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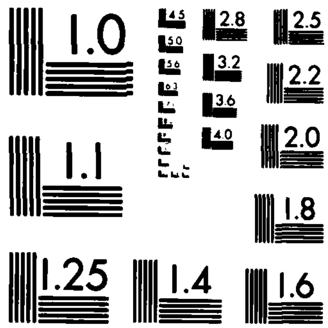
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AIR FORCE LOGISTICS MANAGEMENT CENTER

DEMAND FORECASTING

BY

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ABSTRACT

This study offers an analysis of alternative approaches to forecast both demand averages and demand variation. The analysis has four main parts; comparison of alternative forecasting techniques, statistical analysis of Air Force Economic Order Quantity item's demand patterns, determination of the stockage and operational performance of alternative forecasting techniques, and determination of the impact of the recommended stockage policy change on the Air Force stock fund.

EXECUTIVE SUMMARY

The purpose of this study is to analyze and develop alternative forecasting techniques for both demand averages and demand variation for Economic Order Quantity (EOQ) items. Currently demand average forecasts are used to determine the operating level and order and ship time (O&ST) quantity. An estimate of demand variation is currently used to compute the safety level quantity.

We compare the current and alternative forecasting techniques using demand histories simulated over 50 years. We found the current method provides as accurate an estimate of average demand as any other method we tested. HOWEVER THE CURRENT SYSTEM'S ESTIMATE FOR DEMAND VARIATION IS INADEQUATE.

Statistical analysis of actual Air Force EOQ item's demand history supports the conclusion that estimates of demand variation are inadequate. The current system assumes that demand variance is three times the demand average, i.e., a variance to mean ratio of 3. Actually the average variance to mean ratio is 25. Thus the current system underestimates the demand variance for over 40% of the Air Force EOQ items.

We compare six alternative methods for estimating and using demand variation. We use the System to Analyze and Simulate Base Supply (SASBS) model to evaluate the effectiveness and efficiency of the six alternative techniques. The method that computes the actual variance of demand and order and ship time and places a ceiling on the safety level is the method we recommend. The recommended method increases the unit fill rate by an average of 14% and decreases grounding incidents an average of 4%.

We recommend the safety level computation at base level be modified to accurately measure demand variation and include order and ship time variation. The recommended method will increase the safety level requirements by $101.0 million; $76 million for General Support Division and $25 million for Systems Support Division. We also present another method which also accurately measures demand and order and ship time variation. This method provide most of the benefits but at reduced costs.

TABLE OF CONTENTS

CHAPTER 1

THE PROBLEM

PROBLEM STATEMENT

a. This is the first of a two-phase report on demand forecasting. This report examines forecasting demand for consumable or economic order quantity (EOQ) items. The second phase will examine demand forecasting for reparable items, and requires completion of the base level reparable stockage policy simulation model.

b. We examined the current and alternative methods to forecast demand for Air Force consumable (economic order quantity) items to answer the following questions:

(1) Which method provides the most accurate measures of demand?

(2) Are the demand forecasts used effectively in the USAF Standard Base Supply System (SBSS) consumable inventory requirement depth model?

(3) What is the performance, operational, and cost impact of alternative methods of demand forecasting?

BACKGROUND

a. The forecast for demand is the biggest factor in determining the depth of stock. The prediction of demand is used in determining both the reorder point, which determines when to order, and the operating level, which determines how much to order. The current system computes a daily demand average, which is basically the average demand per day for the previous 18 months. Daily demand is computed via:

$$\text{Daily Demand Rate (DDR)} = \frac{\text{Cumulative Recurring Demands (CRD)}}{\text{Current Date} - \text{Date of First Demand (DOFD)}}. \qquad (1)$$

All recurring demands for an item are used to calculate the DDR, even demands that occurred more than 18 months ago. These old demands are included by the semiannual updating of the cumulative recurring demands (CRD). For example, if the demand history has been collected for more than 18 months, a DDR is calculated as in (1) above and the following fields are updated:

$$\text{CRD} = \text{DDR} \times 365 \qquad (2)$$

and

$$\text{DOFD} = \text{Current Date} - 365. \qquad (3)$$

The average DDR is used in computing both the operating level and the reorder points.

b. In the current SBSS, the operating level is the most economical amount of stock to perform the day-to-day mission. The operating level is the Wilson Economic Order Quantity based on a one year demand forecast. The equation for the operating level for non-local purchase items is:

$$\text{Operating Level} = 5.9 \sqrt{\frac{\text{DDR X 365}}{\text{Unit Price.}}} \tag{4}$$

The operating level for local purchase items is the same as (4) except that 5.9 is replaced by 11, because of the higher local purchase cost to order expense.

c. The DDR is also used in computing both components of the reorder point; the Order and Ship Time quantity (O&STQ) and the Safety Level Quantity (SLQ). The O&ST quantity is the forecast of the average amount of stock necessary to support customer requirements during the time from submission of a stock replenishment requisition to receipt of the materiel. The equation is:

$$\text{O\&STQ} = \text{DDR X Order and Ship Time.} \tag{5}$$

The Safety Level Quantity is an estimate of the standard deviation of demand during the O&ST. The equation is:

$$\text{SLQ} = \sqrt{3 \text{ (DDR X O\&ST)}}. \tag{6}$$

The safety level is multiplied by a C factor, which is used to set the percentage of time a customer order should be filled during the replenishment cycle. The percentages are shown in Table 1-1.

C Factor Percentages

Standard Deviation C Factor	Percentage
1	84
2	97
3	99

Table 1-1

CHAPTER 2

ANALYSIS

OVERVIEW: We document our analysis in four sections. The first section describes an analysis of demand data. We show the results of testing alternative forecasting methods using simulated demand histories which were based on actual Air Force demand data. In the second section, we summarize our statistical data analysis on actual Air Force data. In the third section, we compare the stockage and operational performance of alternative forecasting techniques to the current system using the System to Analyze and Simulate Base Supply (SASBS). Finally, we discuss some other factors bearing on the problem.

In this chapter we summarize our analysis. For technical details of our analysis refer to appendices where appropriate.

ALTERNATIVE FORECASTING METHODS

One of the biggest problems with comparing alternative forecasting techniques is the lack of sufficient data. Normally one would like at least 10 years of demand history for an item to test the performance of a forecasting technique. This is especially true for items that have relatively few demands (less than one demand per month), which is common in the Air Force. To solve this problem, we selected a sample of 20 items (see Appendix A) and used their actual demand histories over a one year period. Then for each item, we computed an empirical demand distribution. For example, if an item had five orders in a year and two orders were for one each and 3 orders were for two each then the probability distribution is:

Demand Size	Probability of Demand
1	2/5 = .40
2	3/5 = .60

We then simulated 50 years of demand history using the empirical probability distribution of demand. As a result we have 50 years of demand history for 20 items which display demand patterns representative of Air Force EOQ items.

Using these demand histories we compared the performance of six forecasting methods (see Table 2-1). Four of the methods use exponential smoothing, which is a widely used simple method to forecast demand. The exponential smoothing model develops a monthly forecast demand which is;

$$\alpha \text{ (Actual Demand)} + (1 - \alpha) \text{ Previous Month's Forecast.} \qquad (7)$$

The alpha (α) symbol is called a smoothing constant and is a number between 0 and 1. The closer the α value is to 1, the more weight given to the most recent actual demand. We tested four α values ranging from .05 to .20. The other two methods are variants of the current Standard Base Supply System (SBSS) forecasting method. The method SBSS6 computes a demand forecast every six months while the method SBSS1 computes a new forecast every month.

FORECASTING METHODS

FORECAST METHOD	DESCRIPTION
ES.05	Exponential Smoothing with $\alpha = .05$.
ES.10	Exponential Smoothing with $\alpha = .10$.
ES.15	Exponential Smoothing with $\alpha = .15$.
ES.20	Exponential Smoothing with $\alpha = .20$.
SBSS6	Standard Base Supply System method with new forecasts computed every 6 months.
SBSS1	Standard Base Supply System method with new forecasts computed every month.

Table 2-1

We compare the forecast methods by comparing the mean absolute deviation (MAD), which is the average amount of the absolute value of the difference between the forecast and actual demand. Table 2-2 displays the summary of the results (see Appendix A for details).

MEAN ABSOLUTE DEVIATION FOR FORECASTING METHODS

FORECAST METHOD	MAD
ES.05	57.4
ES.10	57.8
ES.15	58.6
ES.20	59.4
SBSS6	57.3
SBSS1	57.4

Table 2-2

We also compared the percentage of time an erroneous forecast would have caused a stock out condition for each forecasting method. We compare each of the six methods in Table 2-1 to the current SBSS baseline. To compare stock out performance for the six methods, we need to compute a safety level quantity. We use a safety level quantity [2] of

$$(1.2533 \times \text{MAD}). \tag{8}$$

The SBSS baseline method uses the safety level shown in equation (6). Table 2-3 summarizes those results in two areas; those items with low demand variance and those items with high variance (see Appendix A).

STOCK OUT PERCENTAGE COMPARISON

FORECAST METHOD	STOCK OUT PERCENTAGE LOW VARIANCE	HIGH VARIANCE
Baseline	17.9%	31.4%
ES.05	16.9	16.1
ES.10	17.0	16.2
ES.15	16.9	16.2
ES.20	17.0	16.4
SBSS6	17.7	16.0
SBSS1	17.3	16.1

Table 2-3

Note from Table 2-2 that the SBSS methods work as well or better than exponential smoothing forecasting methods and that exponential models with small smoothing constants perform better. These findings agree with previous AFLMC research findings [7]. Table 2-3 shows that the current systems estimate of the variance of demand is not accurate and does not perform well for high variance items. Currently, the actual percentage of stock outs for high variance items is over 30%. Current SBSS policy indicates the stock out percentage should be 16%, however, due to the current system's poor forecast of demand variance the policy goal is not being met.

The above analysis shows that the adaptations of the current system have the minimum MAD for stationary demand distributions. We also test the forecasting methods for non-stationary demand distributions, that is distributions where the average demand is either increasing or decreasing. Table 2-4 summarizes the MAD results with trended data. Table 2-5 summarizes the percentage of stock outs for each forecasting method for trended data.

MEAN ABSOLUTE DEVIATION FOR TRENDED DEMAND DATA

FORECAST METHOD	MAD INCREASING TREND	DECREASING TREND
ES.05	64.3	50.7
ES.10	65.0	50.4
ES.15	66.2	50.7
ES.20	67.0	51.0
SBSS6	68.4	51.1
SBSS1	68.2	50.6

Table 2-4

STOCK OUT PERCENTAGE FOR TRENDED DEMAND DATA

FORECAST METHOD	STOCK OUT PERCENTAGE			
	LOW VARIANCE		HIGH VARIANCE	
	Positive Trend	Negative Trend	Positive Trend	Negative Trend
Baseline	26.0	21.0	44.7	35.2
ES.05	14.8	11.8	18.4	13.0
ES.10	15.7	13.6	18.1	13.8
ES.15	16.7	15.0	17.5	14.3
ES.20	16.9	15.6	17.5	14.6
SBSS6	21.5	18.9	22.2	17.7
SBSS1	22.1	21.0	23.3	20.7

Table 2-5

Table 2-4 shows that exponential smoothing models with small α values have smaller MAD than the SBSS model, especially for increasing demand patterns. The exponential smoothing models also tend to have fewer stock outs. However, we also measure the average amount of stock necessary to achieve these reduced stock out percentages. The ES.05 method requires a 26% increase in stock over the SBSS6 method. In other words for trended data the ES.05 method requires considerably more stock for a slight reduction in stock out percentage. Additionally previous academic studies conducted for the AFLMC indicate, "the distribution of demands shows no pattern except that they tended to be very sparse and erratic"[5]. Our empirical review of demand data supports the conclusion that Air Force item demand patterns have little or no discernable trend, but instead are erratic; demands occur infrequently and for varying amounts. Thus a forecasting technique that tends to stabilize demand forecasts is appropriate. This is supported by our findings that the SBSS method and exponential smoothing models with low α values perform the best. For trended data, one would expect exponential smoothing models with higher α values to respond to the trend quicker and therefore provide better estimates. However as noted in Table 2-4, exponential smoothing models with low α values perform better which is due to the erratic nature of the demand. Further in the absence of trended data, the SBSS forecasting method is equal to or superior than other commonly used inventory forecasting models.

We should note here that there are other forecasting models. In fact there are numerous academic and Air Force studies comparing alternative forecasting models. We list other forecasting methods in Appendix B and indicate our reason for not testing these methods. This study compares the most appropriate forecasting models for Air Force retail level inventory application.

STATISTICAL DATA ANALYSIS

In this section, we examine the statistical properties of demand data, in particular the variance of demand. The current system assumes the variance of demand is three times the average demand. This quantity is multiplied by the order and ship time and the square root of that product provides the safety level quantity (see equation 6). Thus the safety level quantity is the estimate of the standard deviation of demand for a specified order and ship time. We noted in the Alternative Forecasting Methods Section that the current systems estimate of the variance was not accurate and therefore ineffective for high variance items. In this section we measure the actual variance for Air Force inventory items.

Table 2-6 shows the actual average variance-to-mean ratio (VMR) for consumable items from five AF bases. Note the average VMR is significantly

VARIANCE-TO-MEAN RATIO

BASE	AVERAGE VARIANCE-TO-MEAN RATIO
Upper Heyford	14.2
Kunsan	27.6
Little Rock	21.7
Randolph	30.2
England	29.5

Table 2-6

higher than 3, which the current system uses to estimate demand. Figure 2-1 provides a relative frequency diagram for the VMR at Little Rock, which is representative of all the bases we examined.

VARIANCE-TO-MEAN RATIO
LITTLE ROCK

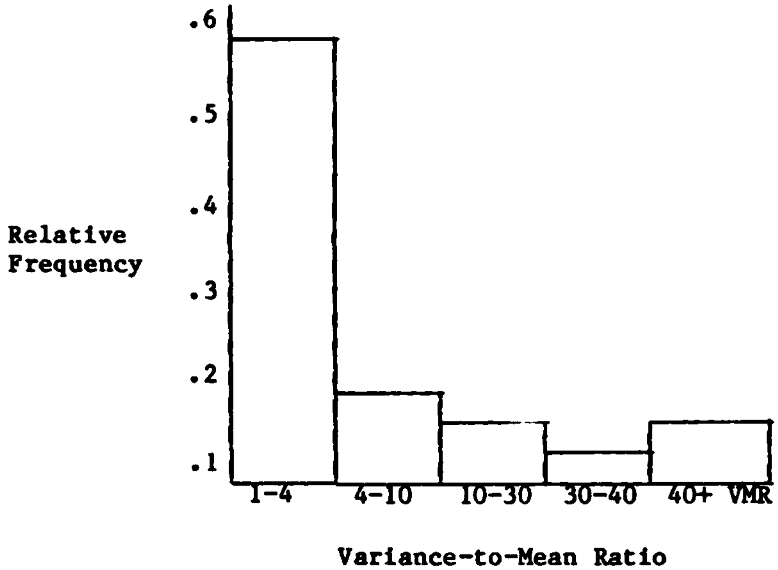

Figure 2-1

As Figure 2-1 shows, the current system provides an accurate estimate for fewer than 57% of the Air Force consumable items. THE CURRENT SYSTEM DOES NOT ACCURATELY *MEASURE DEMAND* VARIABILITY WHICH RESULTS IN INEFFECTIVE STOCKAGE FOR OVER 40% OF AF CONSUMABLE ITEMS.

Next we examined items with very high VMR. We define items with high VMR to be items with VMR greater than 100. Items with high VMR may result in a safety level quantity over twice as large as average demand during a leadtime (which is the order and ship time quantity). Before significantly increasing the amount of safety stock for these items, we examined their demand pattern. We found 34% (26 out of 75) of the items had VMR greater than 100, and that for 38% (10 out of 26) of those items the safety level quantity would be considerably inflated. Table 2-7 shows the demand pattern for three of those items requiring a significantly large safety level.

DEMAND PATTERNS

ITEM	MONTHLY DEMAND PATTERN 1	2	3	4	5	6	7	8	9	10	11	12	VMR
A	0	0	0	0	0	50	0	0	0	0	326	0	258
B	0	0	0	22	4	504	6	2	4	0	4	2	419
C	10	82	4	28	5	32	395	3	0	0	0	0	248

Table 2-7

As Table 2-7 shows the high VMR are caused by an unusually high demand occurrence. These occurrences should be considered outliers, and we should not stock for these occurrences (see Appendix C). Therefore we should either filter out these large occurrences or place a ceiling on the amount of safety stock to support these items.

STOCKAGE AND OPERATIONAL PERFORMANCE

We tested six different methods of using demand and order and ship time forecasts for computing inventory levels and compared them to the current "baseline" method. We describe the six methods in Table 2-8 and Appendix D. The methods tested are attempts to improve the current system's forecast of demand and O&ST variability. As shown in our section on forecasting methods and our Follow-on Order and Ship Time Report, the current forecast for demand and O&ST averages are as accurate as any other methods we tested.

FORECASTING METHODS FOR SIMULATION

METHOD	DESCRIPTION
Regression for Variance of Demand (RVD)	This method uses the formula; Demand Variance = 3 (Average Demand)$^{1.62}$, which was found via regression (see Appendix D).
Regression for Variance of Demand and Order and Ship Time (RVDOST)	This method uses the formula for demand variance as above and also includes the variance of Order and Ship Time in the safety level computation.
Variance of Demand (VARD)	This method computes the actual variance of demand based on historical demand data (see Appendix D).
Variance of Demand and Order and Ship Time (VARDO)	This is the same as the above method only it includes O&ST variance.
Variance of Demand with Ceiling (VARDC)	This is the same as the VARD method except that the safety level quantity cannot exceed (C X 2 X O&STQ).
Variance of Demand and Order and Ship Time with with Ceiling (VARDOC)	This is the same as the VARDO method except that the safety level quantity cannot exceed (C X 2 X O&STQ).

Table 2-8

In Table 2-9, we show the percent increase (or decrease) from the current system (baseline) for Kunsan Air Force Base. We present the results from Upper Heyford, Little Rock, Minot, and England in Appendix E. Table 2-9 shows the significant increase in fill rates, especially in the unit fill rates. Note that placing a ceiling on the safety level does not significantly lower the effectiveness, but it does significantly reduce cost. The reason is the high safety levels are usually caused by "unusual" demands (reference Table 2-7) and these demands cannot be satisfied even if we increase the safety stock. Table 2-9 also provides efficiency measures, for example the MICAP efficiency measure provides the percent decrease in MICAP per percent increase in on hand inventory. Efficiency measures the amount of bang for the buck!

SIMULATION RESULTS

(KUNSAN)

PERCENT CHANGE OVER CURRENT SYSTEM

CATEGORY	RVD	RVDO	VARD	VARDO	VARDC	VARDOC
Line Item Fill Rate (All Items)	6.7%	8.7%	8.1%	9.4%	7.6%	8.9%
Line Item Fill Rate (Stocked Items)	7.2	9.2	8.6	10.0	8.1	9.5
Unit Fill Rate (All Items)	5.6	8.9	36.9	37.7	35.6	36.3
Unit Fill Rate (Stocked Items)	5.9	9.4	28.8	29.5	27.4	28.2
OH Inventory	10.9	17.9	30.7	33.3	18.0	20.5
MICAP	0	0	-3.0	-3.0	-3.0	-3.0
Efficiency:						
MICAP % / OH Inventory %	0	0	-.098	-.090	-.167	-.146
Unit Fill Rate % (Stocked Items) / OH Inventory %	.541	.525	.938	.886	1.522	1.376

Table 2-9

The results in Table 2-9 are representative of the results shown in Appendix E. In virtually every case, the efficiency is higher for methods with a ceiling on the safety level. At one base the efficiency for methods that include Order and Ship Time variation is greater than those without O&ST variation. At all the other bases the efficiency is slightly less with the inclusion of O&ST variation. Nonetheless there is some improvement with O&ST variability without much increase in inventory investment.

OTHER FACTORS

Before we make conclusions and recommendations, we note four factors.

a. First in our report entitled Follow-on Order and Ship Time Study, we recommended we analyze alternative measures of Order and Ship Time (O&ST)

using Federal Supply Groups (FSG) and Classes (FSC). Per our discussion of Table 2-9 above this analysis is no longer necessary. Our previous analysis indicated that for some sources of supply, O&ST averages were different for different FSGs and FSCs. However, average order and ship time and the variance of order and ship time have much less impact than the measures of the average and variance of demand. A more accurate measure of order and ship time will not significantly improve performance as we had initially thought.

b. The second factor is that DODI 4140.45 directs that the safety level be less than or equal to the order and ship time quantity. As documented above, our data analysis indicates Air Force's retail level item demand patterns are erratic, which means many items have a large variance of demand. Per DODI 4140.44, the safety level is the amount of stock necessary to meet the variability of demand and order and shipping time to minimize total variable costs for any given supply performance. The Air Force policy for supply performance during a reorder cycle is 84% and UNLESS WE ACCURATELY MEASURE THE VARIANCE OF DEMAND WE WILL NOT MEET THE AIR FORCE GOAL. In order to comply with DODI 4140.44 policy, DODI 4140.45 must be changed.

We determined the percent of items where the safety level quantity would exceed the order and ship time quantity with the current method and our proposed method to compute the safety level quantity. We present the results in Table 2-10. We assumed both a 17 day and 34 day O&ST with a standard deviation of 8.4 and 17 days which was based on actual data from England AFB. Note even with the current system that for the majority of the items the safety level quantity exceeds the Order and Ship Time Quantity. We do believe there should be a ceiling on the safety level for cost efficiency, however we recommend the ceiling be:

C X 2 X O&STQ,

where C is the SBSS C factor.

SAFETY LEVEL VS ORDER AND SHIP TIME QUANTITY

SAFETY LEVEL	17 DAY O&ST AVERAGE SLQ	17 DAY O&ST PERCENT OF ITEMS WHERE SLQ > O&STQ	34 DAY O&ST AVERAGE SLQ	34 DAY O&ST PERCENT OF ITEMS WHERE SLQ > O&STQ
Current Method:				
Maximum ($\sqrt{3 \times O\&STQ}$, 15 x DDR)	5.99	72%	6.56	59%
Proposed Method:				
Minimum (Standard Deviation Demand and Order and Ship Time, 2 x O&STQ)	9.93	95%	16.42	88%

Table 2-10

c. The third factor is to determine the General and the Systems Support Division stock fund monies required to implement the proposed safety level computation method. Unfortunately current supply and stock fund reports do not break out the safety level quantity for EOQ assets. Thus we had to go through a few steps to approximate the stock fund impact. Appendix F describes the process. Our best estimate for the General Support Division is $75.76 million and for the Systems Support Division is $25.35 million.

d. Our fourth factor is due to the relatively large increase in stock fund requirements. We analyze the performance and stock fund impact with an alternative method. This method accurately measures demand and order and ship time variation but reduces the safety level stock required. We analyze this other method to try to reduce the costs of implementation. For example if sufficient funds are not available for full scale implementation, then this method could be implemented pending additional funding. The method is reducing the safety level ceiling to 2 X O&STQ.

(1) We show in Table 2-7 and Appendix C the impact of unusually high demands on the variability of demand and the safety level quantity. For many of these types of demand patterns increasing the safety level quantity will not increase support. Therefore, we examine the performance impact of limiting the safety level quantity to 2 X O&STQ. This only affects overseas bases where C=2. Table 2-11 provides the results.

SIMULATION RESULTS
USING A C FACTOR OF 2 AND A SAFETY LEVEL CEILING OF
2 X O&STQ

PERCENT CHANGE OVER CURRENT SYSTEM

CATEGORY	KUNSAN	UPPER HEYFORD
Line Item Fill Rate (All Items)	6.6%	4.7%
Line Item Fill Rate (Stocked Items)	7.0	5.0
Unit Fill Rate (All Items)	34.4	14.5
Unit Fill Rate (Stocked Items)	26.2	11.6
OH Inventory	7.9	-1.3
MICAP	-3.0	-11.1

Table 2-11

Comparison of Table 2-11 with Table 2-9 and Table E-1 shows we achieve almost all the benefit of the higher safety level ceiling at much less cost.

(a) Using the same process (as shown in Appendix F) to estimate the stock fund impact, by lowering the safety level ceiling to 2 X O&STQ our best estimate for the increase in General Support Division (GSD) is $57.6 million and for the increase in Systems Support Division (SSD) is $19.3 million. This is a $18 million decrease in GSD and $6 million decrease in SSD with almost the same benefit as the method that uses C X 2 X O&STQ for the safety level ceiling.

(b) Note we recommend the DOD policy be set so the safety level ceiling be:

C X 2 X O&STQ.

However, a ceiling of 2 X O&STQ could be used for all but mission essential items, where the C factor could be increased. Thus, the higher ceiling would be necessary for mission essential items and thus should be allowed by DOD policy.

CHAPTER 3

CONCLUSIONS/RECOMMENDATIONS

CONCLUSIONS

a. The current demand forecasting method provides a satisfactory average demand estimate for Air Force item's demand patterns.

b. THE CURRENT SYSTEM'S DETERMINATION OF THE SAFETY LEVEL QUANTITY IS INADEQUATE. It underestimates demand variation for over 40% of Air Force EOQ assets and does not consider order and ship time variation at all.

c. The DOD policy constraining the safety level quantity (DODI 4140.45) limits the Air Force from meeting its stated stockage policy objective.

d. The Air Force can decrease MICAP occurrences by an average of 4% and increase unit fill rate by an average of 14% (i.e. new fill rate = 1.14 old fill rate) by including an accurate measure for the variation of demand and order and ship time in the computation of the safety level.

e. Placing a ceiling on the safety level of two times the order and ship time quantity at all bases, both CONUS and overseas bases, provides nearly all the benefits and significantly reduces the cost of implementing a safety level which accurately measures demand and order and ship time variability.

RECOMMENDATIONS

a. Implement a system that accurately measures demand and order and ship time variation. We recommend the method that:

(1) Computes the variance of demand via:

$$\text{Variance of Demand} = \frac{\sum \text{Demand}^2 - \frac{[\sum \text{Demand}]^2}{n}}{n}$$

where;

$\sum$ Demand = Cumulative Recurring Demands (CRD),

$\sum \text{Demand}^2$ = the sum of the demands squared, and

n = number of days since date of first demand.

(2) Computes the safety level via:

$$\text{Safety Level} = C\sqrt{\text{O\&ST (Variance of Demand)} + \text{DDR}^2\text{ (Variance of O\&ST)}}$$

where;

C = the SBSS C factor,
DDR = daily demand rate, and
O&ST = Order and Ship Time.

(3) Uses a ceiling of the safety level of:

C X 2 X O&STQ.

(OPR: HQ USAF/LEYS).

b. Should Phase IV delay implementation of our recommendation, implement in the interim the regression based method (RVD) which requires changing only one variable in the current system. (OPR: HQ USAF/LEYS).

c. Change DOD policy (DODI 4140.45) from limiting the safety level quantity to be less than or equal to the order and ship time quantity to limiting the safety level quantity to be less than or equal to:

C X 2 X O&STQ.

(OPR: HQ USAF/LEYS.)

APPENDIX A

DATA SAMPLE

APPENDIX A

DATA SAMPLE

1. We analyze alternative forecasting techniques using a sample of 20 actual Air Force item demand histories. This appendix documents that data sample. Table A-1 summarizes the 20 items.

SUMMARY STATISTICS FOR 20 ITEM SAMPLE

Item	Average Number of Orders per year	Average Demand		Variance of Demand	Variance to Mean Ratio
		Daily	Monthly		
1	6	4.23	127	13,689	108
2	42	14.50	174	3,844	22
3	12	20.25	243	17,689	73
4	9	1.00	30	484	16
5	7	3.83	46	1,764	38
6	12	2.33	28	119	4
7	13	38.13	1144	634,938	555
8	4	1.06	32	900	28
9	3	1.93	58	3,600	62
10	3	.10	3	9	3
11	2	1.20	36	2,500	69
12	10	.36	11	76	7
13	3	.46	14	497	36
14	1	.01	.37	.32	.86
15	3	.10	3	12	4
16	3	.56	17	305	18
17	9	.20	6	12	2
18	18	.50	15	53	4
19	5	.06	2	1.4	.71
20	1	.13	4	31	8

Table A-1

2. The average variance to mean ratio is 53, however, if item 7 is removed the average variance to mean ratio is 26.5, which is representative of what we found in our 5 Air Force base sample. Our purpose in selecting the sample was to have a wide spectrum of items in terms of number of orders per year, average demand, and variance to mean ratio. If one item or group of items favored one particular forecasting method, then perhaps different forecasting methods could be used for separate items. However, the performance of the forecasting models was consistent over all the items.

APPENDIX B

FORECASTING METHODS

APPENDIX B

FORECASTING METHODS

1. There are literally hundreds of forecasting methods that could potentially be used for Air Force retail level inventory applications. In this appendix we list some of those methods and explain why we did not evaluate them. Forecasting methods can be grouped into three major areas, qualitative, time series and casual. We provide a summary of these three areas in Table B-1, which was extracted from [1].

FORECASTING METHODS

General Approach: Forecasting Technique	General Description	Applications	Relative Cost
Qualitative: Examples include Delphi, market research and historical analogy.	Uses human judgment and rating schemes to turn qualitative data into quantitative estimates.	Long range forecasts for areas that do not have historical data.	Medium to high
Time Series	Statistical techniques using past data to predict future occurrences.	Use when relationships are clear and stable. Use for inventory control.	
Moving Average	Arithmetic or weighted average of past occurrences.	Inventory	Low
Single Exponential Smoothing	Weight assigned to the latest occurrence and added to previous forecast.	Inventory	Low
Adoptive Exponential Smoothing	Different weights are assigned to the latest occurrence.	Inventory	Low
Double Exponential Smoothing	Two weights are used and assigned to the level and trend of the data.	Inventory	Low
Box-Jenkins	Mathematical model where exponential weights are designed via statistical techniques.	Inventory	Medium
Causal: Examples include regression and econometric models.	Forecast based on one or more intrinsic or extrensic variables (i.e., flying hours).	Product Sales	Medium to high

Table B-1

2. Qualitative methods required human judgment as an input to the forecast. Clearly these methods are not practical for an Air Force retail inventory

account with 10,000 or more EOQ items. Causal models could provide accurate forecast for inventory items, but requires considerable data collection and the availability of statistical models (and people with the technical expertise) at each retail location in the Air Force. The regression model at one base would probably not apply to another base. In fact different regression models would be needed for different classes of items at one base. For example, aircraft parts would be related to flying hours, communication parts for communication activity, and tools to number of mechanics or shops. Thus causal models were not considered practical and were not evaluated for forecasting Air Force EOQ items.

3. Time series models are the most practical models for forecasting Air Force EOQ items. Many academic and empirical studies have analyzed time series models. The results of virtually all these studies is that, "single exponential models are suitable for most items in an inventory control system." The other models ". . . were approximately equal in terms of forecast errors, but increased the amount of data collection and computational time [4,6,3 and 7]." In summary single exponential smoothing models showed the most promise and are the methods we evaluated.

4. We also evaluated the current Standard Base Supply System's (SBSS) forecasting method which is a variant of the moving average method. The moving average model provides the same results as single exponential smoothing model when the parameters are set so;

$$\alpha = \frac{2}{N+1},$$

where α is the exponential model's smoothing parameters and N is the number of periods used in the moving average model. In the SBSS moving average model, N varies depending on the date of first demand. Thus the corresponding α value ranges from .001 for items with many years of past demand history to .29 for items with fewer than 6 months demand history.

APPENDIX C

DEMAND OUTLIERS

APPENDIX C

DEMAND OUTLIERS

1. This appendix describes the impact of large demands on inventory policy and provides the rationale for placing an upper limit on the safety level quantity (SLQ). The SLQ is the amount of stock necessary to provide a specified level of protection to support the mission when demand and order and ship time (O&ST) are uncertain. We use the variance of demand and O&ST as a measure of the uncertainty. Thus the higher the variance, the more uncertainty of demand and leadtime. We use SLQ to establish a reorder point (ROP), where

$$\text{ROP} = \text{Average Demand during an O\&ST} + \text{C} \times \sqrt{\begin{matrix}\text{Variance of Demand} \\ \text{during an O\&ST}\end{matrix}} \quad .$$

2. The value C sets the service level. We use an 84% service level (C=1) for CONUS bases and a 95% service level (C=2) for overseas bases. Figure C-1 depicts the reorder point for an 84% service level.

DEMAND DISTRIBUTION DURING AN O&ST

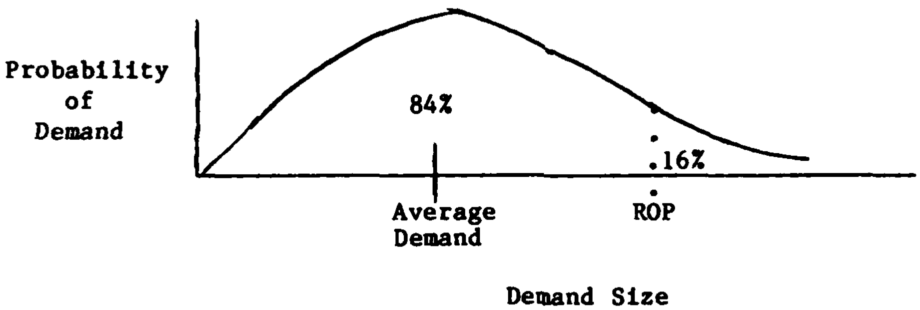

Figure C-1

Note the difference between the ROP and average demand is the safety level or the standard deviation of demand over an O&ST (the square root of the variance of demand over an O&ST). Thus if the variance o: demand over an O&ST is large the safety level is large. In Figure C-2 we examine an actual demand distribution during an O&ST (reference Item B in Table 2-7).

ITEM B
ACTUAL DEMAND DISTRIBUTION

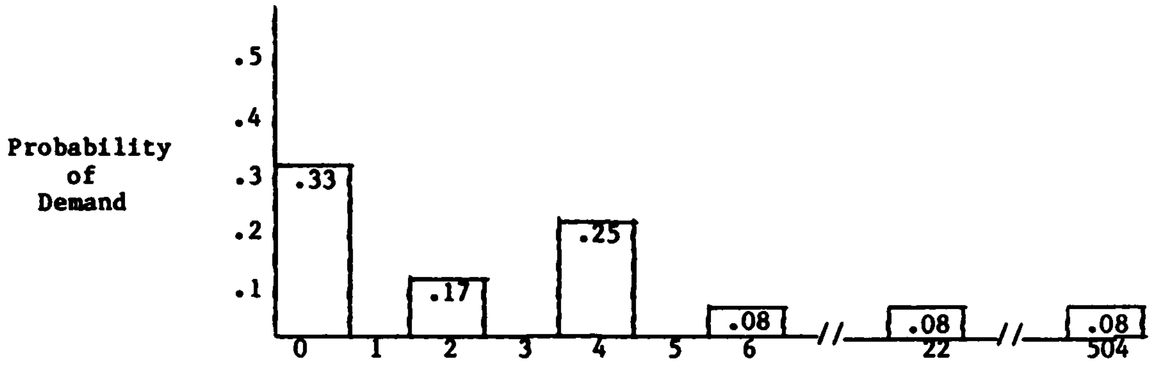

Figure C-2

Average demand for item B is 45.7 and the variance is 19,130.6, thus from (C-1) above the

$$\text{ROP} = 46 + \sqrt{19,130.6} = 184.$$

Note that establishing a reorder point of 184 insures at least 84% of the demands will be satisfied during an O&ST. In fact 92% of the demands will be satisfied. Note if we decrease the safety stock from 138 ($\sqrt{19,130.6}$) to say 92, we are still assured of satisfying 92% of the demands. If item B's demand pattern occurred at an overseas base the safety level quantity would be 276 and still only 92% of the demands would be satisfied.

3. Item B's demand distribution, although it is an actual demand history, presents a "worst" case analysis. However, it clearly portrays that placing a ceiling on the safety levels that are extremely large, will not significantly lower the probability of satisfying a demand during an O&ST. As shown in Table 2-9 and Appendix E, placing a ceiling on the SLQ significantly lowered the amount of stock without reducing operational or stockage effectiveness. We recommend a ceiling for the SLQ of

C X 2 X O&STQ.

This is an easy to implement rule that has a large payoff.

APPENDIX D

VARIANCE ESTIMATION

APPENDIX D

VARIANCE ESTIMATION

1. The purpose of this appendix is to document the methods to compute the variance of demand. We use two methods to compute the variance of demand; regression and statistical formula.

2. We analyze the use of regression to estimate the variance of demand for Air Force retail level EOQ items. Using regression to estimate demand variance has been successful and is currently in use at the AFLC and the Army. We tested several regression estimates using data from five Air Force Bases; Randolph, Kunsan, Little Rock, England, and Upper Heyford. Table D-1 lists the methods we tested and the coefficient of determination (R^2) which is a measure of the effectiveness of the estimation. The coefficient of determination ranges from 0 to 1, with 0 meaning there is no relationship between the variables, and 1 meaning there is a perfect relationship.

REGRESSION METHODS

Regression Equation	Coefficient of Determination
1. $\text{Variance} = b_0 + b_1 \left(\frac{\text{Average Demand}}{\text{Unit Price}}\right)$	.592
2. $\text{Variance} = b_0 + b_1 (\text{Average Demand} \times \text{Unit Price})$	0
3. $\text{Log}(\text{Variance}) = b_0 + b_1 \text{Log}\left(\frac{\text{Average Demand}}{\text{Unit Price}}\right)$	.599
4. $\text{Log}(\text{Variance}) = b_0 + b_1 \text{Log}\left(\frac{\text{Average Demand}}{\text{Unit Price}}\right)^{1/2}$	.599
5. $\text{Variance} = b_0 + b_1 (\text{Average Demand})$	.544
6. $\text{Variance to Mean Ratio} = b_0 + b_1 (\text{Average Demand})$	.598
7. $\text{Variance to Mean Ratio} = b_0 + b_1 \text{Log}(\text{Average Demand})$	.054
8. $\text{Log}(\text{Variance to Mean Ratio}) = b_0 + b_1 \text{Log}(\text{Average Demand})$	.635
9. $(\text{Variance}) = b_0 (\text{Average Demand})^{b_1}$	.936

Table D-1

3. We test regression equation 9 at all five bases and we show the results in Table D-2.

RESULTS OF REGRESSION

Base	Coefficient of Determination	b_0	b_1
Randolph	.936	2.66	1.61
Kunsan	.929	3.55	1.65
Little Rock	.921	2.60	1.61
England	.918	2.83	1.65
Upper Heyford	.926	2.77	1.57

Table D-2

The relatively high coefficient of determination and the consistency of the regression coefficients (b_0 and b_1) indicate the following equation may provide a good estimate of the variance of demand;

$$\text{Variance} = 3\ (\text{Average Demand})^{1.62}.$$

We then test this method with the System to Automate and Simulate Base Supply. The results are shown in the body of the report.

4. We also compute the variance of demand using the statistical formula;

$$\text{Variance of Demand} = \frac{\sum \text{Demand}^2 - \frac{[\sum \text{Demand}]^2}{n}}{n}$$

where n is the number of demand occurrences. In terms of the current SBSS data collection;

$\sum$ Demand = Cumulative Recurring Demands,

$\sum \text{Demand}^2$ = the sum of the demands squared, and

n = number of days since date of first demand.

Thus only one additional data element, Demand^2, needs to be collected by the SBSS.

5. The variance of the order and ship time is measured using the statistical formula for the variance. The safety level is computed by [8]:

$$\text{Safety Level} = C \sqrt{\text{O\&ST (Variance of Demand)} + \text{DDR}^2 \text{ (Variance of O\&ST)}}$$

where;

C = the SBSS C factor,
DDR = daily demand rate, and
O&ST = Order and Ship Time.

For those methods that use only the variance of demand, the variance of O&ST was set to 0.

APPENDIX E

SIMULATION RESULTS

APPENDIX E

SIMULATION RESULTS

(UPPER HEYFORD)

PERCENT CHANGE OVER CURRENT SYSTEM

CATEGORY	RVD	RVDO	VARD	VARDO	VARDC	VARDOC
Line Item Fill Rate (All Items)	4.0	5.5	10.4	11.0	9.3	9.8
Line Item Fill Rate (Stocked Items)	4.2	5.8	10.9	11.5	9.8	10.3
Unit Fill Rate (All Items)	2.8	3.9	17.5	17.6	16.8	17.0
Unit Fill Rate (Stocked Items)	3.0	4.2	14.7	14.8	14.0	14.2
OH Inventory	3.2	9.6	11.6	14.9	7.1	7.1
MICAP	-8.7	-14.3	-7.9	-13.5	-7.9	-13.5
Efficiency:						
$\frac{\text{MICAP \%}}{\text{OH Inventory \%}}$	-2.719	- 1.490	- .681	- .906	-1.127	- 1.901
$\frac{\text{Unit Fill Rate \% (Stocked Items)}}{\text{OH Inventory \%}}$	.938	.438	1.267	.993	2.0	2.0

Table E-1

APPENDIX E

SIMULATION RESULTS

(LITTLE ROCK)

PERCENT CHANGE OVER CURRENT SYSTEM

CATEGORY	RVD	RVDO	VARD	VARDO	VARDC	VARDOC
Line Item Fill Rate (All Items)	.8	.9	1.1	1.2	.7	.8
Line Item Fill Rate (Stocked Items)	.9	1.0	1.2	1.3	.7	.8
Unit Fill Rate (All Items)	.5	.6	5.6	6.3	5.3	6.0
Unit Fill Rate (Stocked Items)	.5	.7	5.0	5.6	4.7	5.3
OH Inventory	4.3	4.0	5.0	5.7	1.5	1.9
MICAP	-5.6	-1.4	-4.2	-5.6	-4.2	-4.2
Efficiency:						
MICAP % / OH Inventory %	-1.302	- .350	- .84	- .982	-2.80	-2.210
Unit Fill Rate % (Stocked Items) / OH Inventory %	1.0	.857	1.12	1.12	1.128	1.132

Table E-2

APPENDIX E

SIMULATION RESULTS

(ENGLAND)

PERCENT CHANGE OVER CURRENT SYSTEM

CATEGORY	RVD	RVDO	VARD	VARDO	VARDC	VARDOC
Line Item Fill Rate (All Items)	.7	1.0	.9	1.0	.5	.5
Line Item Fill Rate (Stocked Items)	.7	1.1	1.0	1.1	.5	.5
Unit Fill Rate (All Items)	.3	1.8	14.8	15.0	14.5	14.6
Unit Fill Rate (Stocked Items)	.3	2.0	12.7	13.0	12.5	12.6
OH Inventory	5.7	6.9	3.4	4.0	.1	.5
MICAP	0	0	0	0	0	0
Efficiency:						
MICAP % / OH Inventory %	0	0	0	0	0	0
Unit Fill Rate % (Stocked Items) / OH Inventory %	.052	.289	3.735	3.25	125.0	25.2

Table E-3

APPENDIX E

SIMULATION RESULTS

(MINOT)

PERCENT CHANGE OVER CURRENT SYSTEM

CATEGORY	VARD	VARDO	VARDC	VARDOC
Line Item Fill Rate (All Items)	2.6	2.6	2.1	2.1
Line Item Fill Rate (Stocked Items)	2.7	2.8	2.2	2.2
Unit Fill Rate (All Items)	13.5	13.5	12.8	13.0
Unit Fill Rate (Stocked Items)	10.6	10.6	9.9	10.1
OH Inventory	8.4	8.9	.5	.7
MICAP	0	0	0	0
Efficiency:				
MICAP % / OH Inventory %	0	0	0	0
Unit Fill Rate % (Stocked Items) / OH Inventory %	1.262	.840	19.8	14.43

Table E-4

APPENDIX F

STOCK FUND IMPACT

APPENDIX F

STOCK FUND IMPACT

1. We determine the increase to the General Support Division (GSD) and Systems Support Division (SSD) stock fund required to implement the proposed changes. Unfortunately, the amount of money invested in the safety level for XB3 items is not segregated in stock fund or supply reports. We first had to determine the investment for the safety level for XF3 items and subtract that from the total GSD and SSD stock fund totals for the safety level. Once we obtain the XB3 safety level requirements, we determine the increase requirements due to our proposed changes. Since the impact is dependent on the C factor and order and ship time, we determine the change for CONUS, Pacific, and European bases. Table F-1 provides the number of CONUS, Pacific, and European bases.

BREAK OUT OF BASES BY O&ST STANDARD

Bases	Standard O&ST	C Factor	Number
CONUS	31	1	86
PACAF	84	2	11
Europe	69	2	19

Table F-1

2. The calculation of the incremental dollar requirements for GSD and SSD is shown below.

GSD	SSD	
$ 17.1	$48.1	Total Demand Level for XF3 (Source: M32).
		Step 1:
X .721	X .721	Multiple factor based on C factor; .687 of XF3 level is SLQ for CONUS and .815 of XF3 level is SLQ for overseas. Weighted average: (86/116 x .687) + (30/116 x .815) = .721.
12.33	34.68	This calculation provides the XF3 SLQ.
77.89	56.62	The Air Force's total SLQ (Source: GSD and SSD Consolidated Stratification and Transaction Report A/031 Dec 83).
		Step 2:
65.56	21.94	Subtracting the XF3 SLQ from the total SLQ provides the XB3 SLQ.
		Step 3:
		The SLQ increase due to the proposed change varies by the O&ST. The increase factors by O&ST are:
		1.66 for CONUS, 3.10 for PACAF, and 2.73 for Europe.
		Step 4:
		These are weighted by the number of bases in CONUS, PACAF, and Europe. The number of overseas bases is doubled due to the C factor, therefore the weights are:
64.10	21.45	.589 (86/146) for CONUS,
30.69	10.27	.151 (2 x 11/146) for PACAF, and
46.53	15.57	.260 (2 x 19/146) for Europe.
141.32	47.29	Total SLQ with our proposal.
$ 75.76	$25.35	To determine the incremental increase we subtracted the total for the XB3 SLQ from the total SLQ for our proposal.

3. We use the same procedure to calculate the stock fund impact of implementing the proposed changes and using a safety level ceiling of 2 X O&STQ for all bases. The only difference is step 3. The increase factors by O&ST are:

1.66 for CONUS,
2.51 for PACAF, and
2.01 for Europe.

Step 4 totals are:

GSD	SSD	
64.10	21.45	CONUS
24.85	8.32	PACAF
34.26	11.46	Europe
123.21	41.23	Total SLQ
$57.65	$19.30	Incremental Increase

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